Forecasting Realized Gold Volatility: Is there a Role of Geopolitical Risks?

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Abstract

We use a quantile-regression heterogeneous autoregressive realized volatility (QR-HAR-RV) model to study whether geopolitical risks have predictive value in sample and out-of-sample for realized gold-returns volatility estimated from intradaily data. We consider overall geopolitical risks along with a decomposition into actual risks (i.e., acts) and threats, and we control for overall the impact of economic policy uncertainty (EPU). We find that, after controlling for EPU, the components of geopolitical risks have predictive power for realized volatility mainly at a longer forecast horizon when we account for the potential asymmetry of the loss function a forecaster uses to evaluate forecasts.

Keywords: Gold-price returns; Realized volatility; Geopolitical risks; Forecasting

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1 Introduction

The role of gold as a “safe haven" is well-recognized. In other words, during periods of heightened risks in other financial markets (Baur and Lucey 2010, Baur and McDermott 2010, Reboredo 2013a, b, Agyei-Ampomah et al. 2014, Gürgün and Ünalmis 2014, Beckmann et al. 2015), general economic uncertainty (Bouoiyour et al. 2018, Beckmann et al. 2019), and geopolitical risks (Baur and Smales 2018), gold provides portfolio-diversification benefits. Naturally, forecasting volatility of gold returns is of interest to investors in the pricing of related derivatives as well as for devising hedging strategies. Understandably, there exists a large literature that has aimed to forecast gold volatility (see, Pierdzioch et al. 2016, Fang et al. 2018 for detailed literature reviews). In general, while earlier studies have primarily utilized a wide-variety of models from the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-family, more recent papers have also use mixed-frequency and boosting approaches to accommodate for the role of a wide variety of information from macroeconomic and financial variables while also controlling for model uncertainty.

Realizing that rich information contained in intraday data can produce more accurate estimates and forecasts of daily volatility (for a detailed discussion in this regard, see Degiannakis and Filis 2017), we aim to extend the existing literature by forecasting the realized volatility (RV) of gold returns (derived based on 5 minute-interval intraday data), using a modified version of the Heterogeneous Autoregressive (HAR) model developed by Corsi (2009). In particular, we augment the basic HAR-RV model with information on geopolitical risks, over and above macroeconomic uncertainty, for the daily period from 3rd December, 1997 to 2000 to 30th May, 2017. In addition, in order to study the entire conditional distribution of the volatility of gold returns, rather than just its conditional mean, we use a quantile regression version of the HAR-RV (QR-HAR-RV). To the best of our knowledge, this is the first paper to analyse the role of geopolitical risks in forecasting the entire conditional distribution of realized volatility of the gold market.[1]

[1]In this regard, it should be noted that, while the focus of Baur and Smales (2018) was primarily to analyze

The remainder of the paper is organized as follows: We describe in Section 2 the methods that we use in our empirical analysis. We present our data in Section 3, summarize our empirical results in Section 4, and conclude in Section 5.

2 Methods

Andersen et al. (2012) propose median realized variance (MRV_t) as a jump-robust estimator of integrated variance using intraday data:[2]

$$MRV_t = \frac{\pi}{6-4\sqrt{3}+\pi}\frac{T}{T-2}\sum_{i=2}^{T-1} med\left(|r_{t,i-1}|,|r_{t,i}|,|r_{t,i+1}|\right)^2, \tag{1}$$

where $r_{t,i} =$ is the intraday return i within day t, and $i = 1,..,T$ denotes the number of intraday observations within a day. We consider MRV as our measure of daily realized volatility in order to attenuate the effect of market-microstructure noise and jumps on our results. MRV, as a jump-robust estimator of realized volatility is significantly less biased in the presence of jumps in the price process.

Corsi (2009) has proposed the HAR-RV model as a technique to model and forecast realized volatility. The HAR-RV has become one of the most popular models in the literature on realized volatility because, despite its simple structure, the HAR-RV model captures "stylized facts" of long memory and multi-scaling behavior associated with volatility of financial markets. The benchmark HAR-RV model, for $h-$days-ahead forecasting, is given by:

$$RV_{t+h} = \beta_0 + \beta_d\, RV_t + \beta_w\, RV_{w,t} + \beta_m\, RV_{m,t} + \varepsilon_{t+h}, \tag{2}$$

where $RV_{w,t}$ denotes the average RV from day $t-5$ to day $t-1$, while $RV_{m,t}$ denotes the average RV^j from day $t-22$ to day $t-1$.

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the impact of changes in geopolitical risks on gold returns, using an exponential GARCH (EGARCH) model, they could not detect evidence of any in-sample impact of such risks on gold market volatility.

[2] Researchers commonly use the term volatility to denote the standard deviation of returns. Because there is not risk of confusion, we use in this research the terms realized volatility and realized variance interchangeably.

We use the standard HAR-RV model as our benchmark model for predicting realized-volatility and then add geopolitical risks (GPR) and economic policy uncertainty (EPU) in order to explore whether these two economic variables have any incremental predictive information. Because *changes* in GPR and EPU should capture that new information that are revealed to traders, we use GPR and EPU in first-differences.[3] In analogy to RV, we further consider there weekly and monthly averages of these variables. We consider the following two extended HAR-RV models:

$$RV^{j}_{t+h} = \beta_0 + \beta_d\, RV_t + \beta_w\, RV_{w,t} + \beta_m\, RV_{m,t} + \theta\, EPU_t + \theta_w\, EPU_{t,m} + \theta_m\, EPU_{t,m} + \varepsilon_{t+h}, \tag{3}$$

$$RV^{j}_{t+h} = \beta_0 + \beta_d\, RV_t + \beta_w\, RV_{w,t} + \beta_m\, RV_{m,t} + \theta\, GPR_t + \theta_w\, GPR_{t,m} + \theta_m\, GPR_{t,m} + \varepsilon_{t+h}. \tag{4}$$

While the baseline HAR-RV model and its two extensions are estimated by the ordinary-least squares technique, we also consider a quantile-regression variant of the model. The quantile-regression variant of the HAR-RV model accounts for the possibility that the predictive value of the predictors differs across the quantiles of the conditional distribution of RV. The quantile-regression HAR-RV model is given by:

$$\hat{\mathbf{b}}_q = \arg\min \sum_i \rho_q(RV^{j}_{i+h} - \mathbf{X_i}\mathbf{b}_q), \qquad i = 1, 2, ..., t, \tag{5}$$

where $\rho_q(u)$ denotes the check function, $\rho_q = \varepsilon_{t+h}(q - \mathbf{1}(\varepsilon_{t+h} < 0)$, q denotes a quantile, and $\mathbf{1}$ denotes the indicator function. Furthermore, the vector $\mathbf{b}_q$ denotes the now quantile specific parameters of the HAR-RV models in Eqs. 2, 3, and 4, a hat denotes the estimates of these parameters, and the matrix $\mathbf{X}$ denotes the predictors of the HAR-RV models. Variants of the quantile-regression variant of the HAR-RV model have been studied in recent research by Haugom et al. (2016) and Balcilar et al. (2017), Baur and Dimpfl (2019). For other recent quantile-regressions-based research on several key aspects of gold-price fluctuations, see i.a. Baur (2013), Dee et al. (2013), Ma and Patterson (2013), Zagaglia and Marzo (2013), and Pierdzioch et al. (2015).

[3] In this regard we follow Baur and Smales (2018). However, unlike them, we use EPU instead of the Chicago Board Options Exchange's Volatility Index (VIX), to prevent substantial losses in data.

In order to study out-of-sample predictability of RV, we consider a fixed-length daily rolling-estimatin window. We vary the length of the estimation window between 1000 and 3000 observations. We use the Diebold and Mariano (1995) test to compare forecast accuracy of the HAR-RV models with and without geopolitical risk as a predictor. The test results are computed in the R programming environment (R Core Team 2017) based on the modified Diebold-Mariano test proposed by Harvey, Leybourne and Newbold (1997), we report the p-values calculated using the R package “forecast” (Hyndman 2017, Hyndman and Khandakar 2008). We study the relative forecast errors of the models to account for heteroskedasticity (e.g., Bollerslev and Ghysels 1996).

3 Data

We use intraday data on gold futures traded in NYMEX over a 24 hour trading day (pit and electronic) to construct the daily measure of realized volatility. The futures price data, in continuous format, are obtained from `www.disktrading.com` and `www.kibot.com`. Close to expiration of a contract, the position is rolled over to the next available contract, provided that activity has increased. Daily returns are computed as the end of day (New York time) price difference (close to close). In the case of intraday returns, 1-minute prices are obtained via last-tick interpolation (if the price is not available at the 1-minute stamp, the previously available price is imputed). 5-minute returns are then computed by taking the log-differences of these prices and are then used to compute the realized moments.

Besides the intraday data, we obtain daily data on the EPU of the United States (US),[4] as developed by Baker et al. (2016) based on newspaper archives from Access World New’s NewsBank service. The primary measure for this index is the number of articles that contain at least one term from each of 3 sets of terms namely, economic or economy, uncertain or uncertainty, and legislation or deficit or regulation or congress or federal reserve or white house.[5]

[4]We understand that gold is a global market, but due to the unavailability of a daily measure of worldwide uncertainty, and the prominent role of the U.S. in the global economy, we use the EPU for the U.S. as a proxy for world uncertainty.

[5]The data is available for download from: `http://policyuncertainty.com/us_monthly.html`.

As far as our main predictor of interest, i.e., the GPR is concerned, it is based on on the work of Caldara and Iacoviello (2018).[6] Caldara and Iacoviello (2018) construct the GPR index by counting the occurrence of words related to geopolitical tensions, derived from automated text-searches in 11 leading national and international newspapers (The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post). They then calculate an index by counting, in each of the above-mentioned 11 newspapers, the number of articles that contain the search terms[7] related to geopolitical risks for every day. Based on the search groups, Caldara and Iacoviello (2018) further disentangle the direct effect of adverse geopolitical events from the effect of pure geopolitical risks by constructing two additional indexes, i.e., the Geopolitical Threats index,[8] and the Geopolitical Acts index[9]

Our analysis covers the daily period of 3rd December, 1997 to 2000 to 30th May, 2017, with the start and end dates being purely contingent on the availability of the intraday data on gold futures.

4 Empirical Findings

Figure 1 displays the results for the benchmark HAR-RV models that we estimate using the ordniary-least-squares techniques. We present results for three different forecast horizons. Specifically, we set $h = 1, 5, 22$ and, thus, study whether the model has predictive value for RV one-day-ahead, five-days-ahead (that is, one week), and 22-days-ahead (that is, approximately one

[6]The data can be downloaded from: `https://www2.bc.edu/matteo-iacoviello/gpr.htm`.

[7]The search identifies articles containing references to six groups of words: Group 1 includes words associated with explicit mentions of geopolitical risk, as well as mentions of military-related tensions involving large regions of the world and a U.S. involvement; Group 2 includes words directly related to nuclear tensions; Groups 3 and 4 include mentions related to war threats and terrorist threats, respectively; Groups 5 and 6 aim at capturing press coverage of actual adverse geopolitical events (as opposed to just risks) which can be reasonably expected to lead to increases in geopolitical uncertainty, such as terrorist acts or the beginning of a war.

[8]This index only includes words belonging to Search groups 1 to 4,

[9] This index only includes words belonging to Search groups 5 and 6.

month). We present results for a quadratic (L2) and a linear loss function (L1). Results show that geopolitical risk improves forecast accuracy relative to the benchmark HAR-RV model, but the results differ across model specifications. For L1 loss, we observe significant test results mainly for the short and medium forecast horizon when we consider the HAR-RV model as our benchmark. The test results for the long forecast horizon become significant once we opt for a relatively long rolling-estimation window. When we consider the HAR-RV-EPU model as our benchmark model, in contrast, we detect improvements in forecast accuracy for the medium and long forecast horizons. Results for threats closely resemble those for geopolitical risks, while the tests for actual realization of risk are only significant when we consider the HAR-RV-EPU model as our benchmark model, and for relatively long rolling-estimation windows. When we consider the L2 loss function, the results are by and large similar to the corresponding results that we obtain for the L1 loss function.

– Please include Figure 1 about here. –

Figure 2 displays the results for the QR-HAR-RV model. For the quantile-regression-based models, we use the check function to compare the forecast accuracy of (relative) forecast errors (that is, a quasi-linear L1 loss function that, depending on the quantile parameter, is asymmetric around zero). This choice of the loss function ensures that we evaluate forecsat errors by means of the same loss function that we use to estimate the quantile-regression model. Results for the short forecast horizon are significant mainyl for a range of quantiles between 0.2 and 0.4 and between 0.6 and 0.8. FOr the medium forecast horizon, test results for all rolling-estimation windows are significant, except for quantiles roughly smaller than 0.2 and larger than 0.8. For the long forecast horizon, the test results are significant for quantiles larger than approximately 0.6, where the width of the area of significant test results depends varies somewhat across rolling-estimation windows. Results are broadly similar for geoplitical risks, threats, and acts.

– Please include Figure 3 about here. –

Figure 3 displays the results we obtain when we control for EPU. For the short forecast horizon, results turn insignificant. For the medium forecast horizon, results (for geopolitical risks and acts) remain significant for several rolling-estimation windows in the range of quantiles between 0.4 and 0.6 (when the rolling-estimation window is not too long). For the long forecast horizon, in turn, the results are very similar to those we obtain when we use the HAR-RV model as our benchmark model.

5 Concluding Remarks

In this paper, we examine the forecasting power of geopolitical risks (over and above economic uncertainty) for the conditional distribution of gold returns volatility, using the quantiles-regression version of the the popular heterogeneous autoregressive realized volatility (HAR-RV) model. Our findings suggest that, after controlling for economy-wide uncertainty, the components of geopolitical risk, i.e., threats and acts, have predictive power for realized volatility, but mainly at a longer forecasting horizon when we account for the potential asymmetry of the loss function a forecaster uses to evaluate forecasts. In sum, our results imply that using information contained in geopolitical risks, investors can improve the design of optimal portfolios involving gold to hedge against primarily long-run risks.

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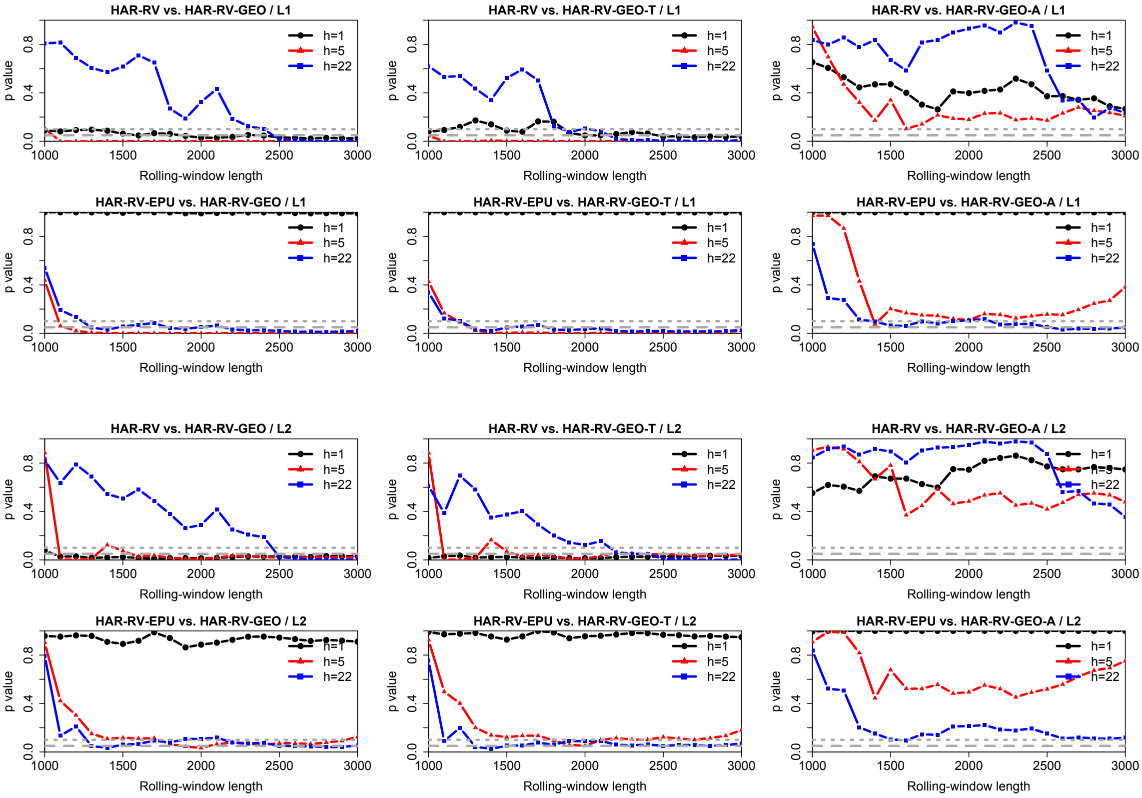
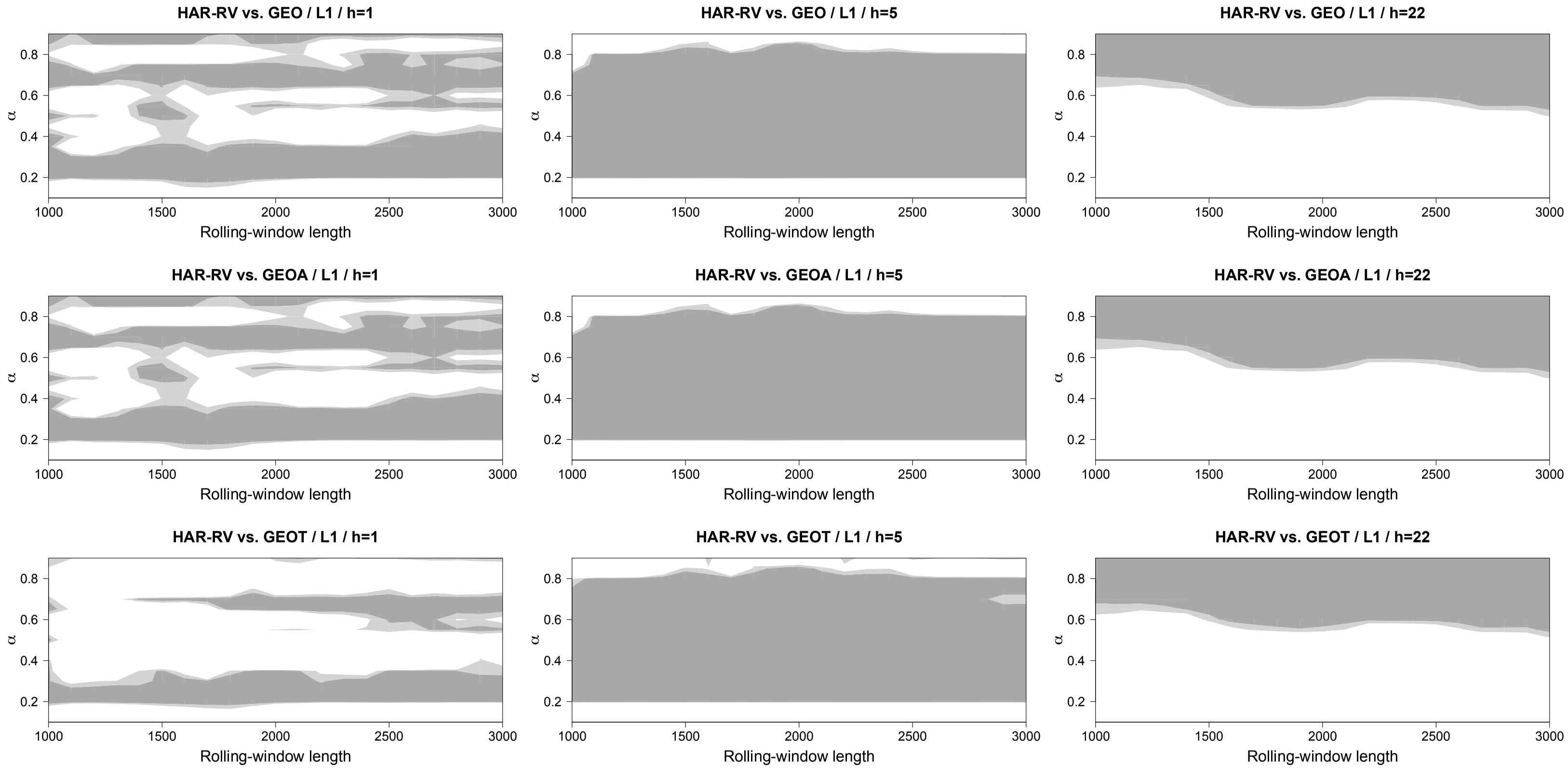
Figure 1: Forecast Comparison (HAR-RV Model)



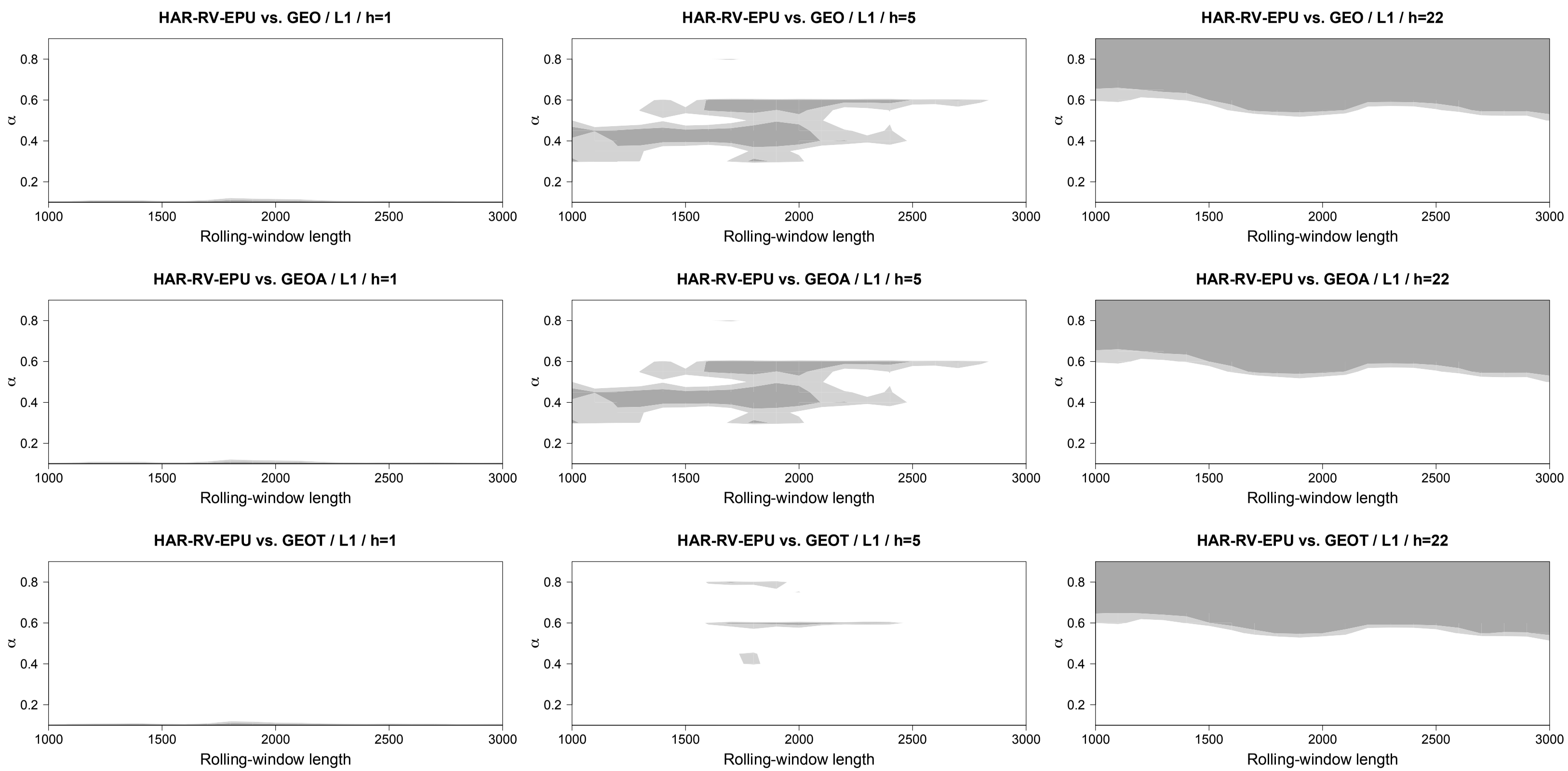
Note: p-values of Diebold-Mariano tests for alternative rolling-window lengths and three different forecast horizons. Results shed light on the accuracy of relative forecast errors. Null hypothesis: the two series of forecasts are equally accurate. Alternative hypothesis: the forecasts from the alternative model are less accurate. The core HAR-RV and the HAR-RV-EPU models are the alternative models. L1: absolute loss. L2: quadratic loss. The loss function is symmetric. The horizontal lines depict the 10% and 5% levels of significance.

Figure 2: Forecast Comparison (QR-HAR-RV Model)



Note: p-values of Diebold-Mariano tests for alternative rolling-window lengths and three different forecast horizons. Results shed light on the accuracy of relative forecast errors. Null hypothesis: the two series of forecasts are equally accurate. Alternative hypothesis: the forecasts from the alternative model are less accurate. The core HAR-RV is the alternative model. The check function is the loss function. The gray (darkgray) areas denote results that are significant at the 10% and 5% levels of significance.

Figure 3: Forecast Comparison (QR-HAR-RV Model With EPU)



Note: p-values of Diebold-Mariano tests for alternative rolling-window lengths and three different forecast horizons. Results shed light on the accuracy of relative forecast errors. Null hypothesis: the two series of forecasts are equally accurate. Alternative hypothesis: the forecasts from the alternative model are less accurate. The HAR-RV-EPU model is the alternative model. The check function is the loss function. The gray (darkgray) areas denote results that are significant at the 10% and 5% levels of significance.